SIMULATION OF AUTONOMOUS VEHICLES BASED ON WIEDEMANN'S CAR FOLLOWING MODEL IN PTV VISSIM

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ABSTRACT
A lot of research deals with capacity effects of autonomous driving, but little is known about the exact driving behavior of autonomous vehicles. Most simulations are based on assumptions regarding the following behavior. Different technical components, that might influence decisively the car following behavior in future vehicles, further complicate the topic. Therefore, there is no common agreement or recommendations on parameter settings when modeling autonomous vehicles in microsimulation software.

We analyzed data of two autonomous vehicles driven in a real-world scenario and compared their following behavior to simulations based on the Wiedemann car following model. We derived the standstill distances and the headway policy of autonomous vehicles from the data. The tests comprised driving in autonomous mode with and without communication between two following vehicles. The simulations show that the behavior of autonomous vehicles communicating with the leading vehicle are reproduced well in Vissim. Problems remain when simulating autonomous vehicles that do not communicate with their leader.

Keywords: Autonomous Vehicles, Connected Vehicles, Car-Following Models, Microscopic Traffic Flow Simulation

INTRODUCTION

In transportation research, it is common understanding that the automation of driving tasks will have a decisive influence on infrastructure capacities. Either positive or negative, it is of urgent importance for transport planning to predict those effects, given the long-life cycles of transport infrastructure.

Simulation is an essential tool in assessing capacities especially on freeways. On freeway links, traffic stability is a major factor for capacity (*1*). When automation changes the following and lane changing behavior, this will probably lead to a different collective behavior regarding traffic flow. Quantifying capacity changes caused by such a fundamental change in driving behavior as automation requires careful modeling and calibration of the driving behavior models. If it is possible to define universally valid models, simulation can allow extrapolation to various driving or context situations, such as varying market penetration rates.

With regard to autonomous driving behavior, the model parameters are seldom tested against real data. Two major problems lead to this situation:

1. Data is not available. Manufacturers of autonomous vehicles (AVs) are competing about a leading position in the technology market and are very restrictive in revealing information about the implementation of their car-following algorithms.
2. Various technical components are under development. So far, it is not clear in which period and combination these components will be relevant in the market. Some manufacturers plan to introduce automation tasks gradually (longitudinal/lateral control) to the market (*2*). Others try to develop new models from scratch which are technically able to drive completely autonomous, i.e. that fulfill the definition of SAE-Level 4 or 5 (*3, 4*). Furthermore, different concepts of communication between vehicles and with infrastructure elements exist (*5*). It is very difficult to make general statements about the technological configurations of the upcoming 20 years.

A lot of research has been done in recent years for making predictions about capacity effects. Some articles focus on a particular technology and/or infrastructure element. In this case, researchers often integrate external controllers into microscopic trafficsimulation tools. A lot of work has been done to investigate effects of Cooperative Adaptive Cruise Control (CACC) on freeway links (*6–8*). Other popular research topics are traffic-actuated control systems using real-time data from automated vehicles (vehicle-to-infrastructure communication) (*9*) and green-light assistance systems (infrastructure-to-vehicle communication) (*10*). Results from these studies cannot be extrapolated to entire transport systems. Others aim at predicting system-wide effects and either estimate effects on a very straightforward level without using microsimulation (*11*) or make general assumptions about the following behavior based on expert opinion (*12*). In contrast to that, Haberl et al. developed a driver model in Matlab/Simulink and integrated it via external driver model in PTV Vissim for simulating different motorway segments and thereby derive macroscopic effects (*13*). The authors also consider the acceptance rate of small time gaps by real drivers via experiments from a driving simulator. Milanes and Shladover published findings from test runs of 4 vehicles that were equipped with ACC and CACC controllers in 2014 (*14*). The CACC controller was developed by the project team itself. In general, little information is given about the source of assumptions when car following models are adjusted. If models are calibrated using real data, the information given is often not representative.

Common assumptions about AV driving behavior are:

- the following time gap for AVs in CACC mode is 0.5 s (*7, 11, 12*)
- the reaction time is almost zero (*7*)
- AVs accelerate and decelerate more smoothly than manually driven vehicles (*15*).

The assumptions on time gaps of autonomous vehicles following a manually driven vehicle vary considerably between one and two seconds (*11, 12, 14*). The different approaches lead to a great variety in the forecasts. On freeways, a capacity increase of up to 300% is forecast by Tientrakool et al. (*16*). Krause et al. calculate a maximum capacity gain of 40% and highlight that capacity losses might occur under small market penetrations (*12*). Friedrich and Shladover predict possible capacity gains on freeways of up to 80% and 100%, respectively (*6, 11*).

For replicating AV behavior exactly, it is feasible to integrate external driver models into a microsimulation program. Nevertheless, for many applications it is more suitable to define car-following models that provide a sufficient approximation of the general behavior of AVs while allowing for easy adjustment to different AV user settings or technological specifications. General models should be able to deliver feasible results on a macroscopic level and can thus be used to predict traffic flow characteristics of AV fleets without knowledge of the respective car following algorithms. Results from simulations based on well-known models are also easy to reproduce. However, the general models used in research on AV capacity effects are usually not tested for validity. We fill this gap with regard to the Wiedemann model by analyzing data from three test vehicles, two of which drive autonomously on a public road in a normal traffic situation. The third car is the leading vehicle and is manually driven. We focus only on the longitudinal behavior of the two autonomous vehicles, looking both at driving with and without communication to the leading vehicle. From the data analysis, we derive requirements for the autonomous driving model behavior and adjust the Wiedemann model's parameters accordingly. We compare the test vehicles' behavior qualitatively to the following behavior of Vissim vehicles and show the goodness of fit and remaining problems for modeling AVs with and without communication.

The data was collected in the course of the CoEXist project (*17*). CoEXist is funded by the European Commission. It aims at, amongst others, enabling traffic software to predict effects of AVs in mixed traffic, i.e. when both autonomous and manually driven vehicles share the roads. The data was collected by TASS International, Netherlands. The test vehicles are three Toyota Prius equipped with a driving logic developed by the research institute TNO (*18*).

The comparison between Vissim following data and observed data shows that the behavior of AVs in CACC is modeled realistically by Vissim. The behavior when driving without communication is much more complicated to reproduce in the simulation, because it deviates from standard human acceleration behavior. We identify current shortcomings and possible improvements in Vissim. The results give insights into which research topics can be analyzed using the current Wiedemann model, and in which fields further improvement is necessary in order to build useful models.

The following section presents the methodology of the data analysis. In the next step, we present insights into the following behavior of AVs and we explain how the Wiedemann model was adjusted to this behavior. Afterwards we compare the empirical data to the Vissim simulation data. Finally, conclusions are summarized, and further work is discussed.

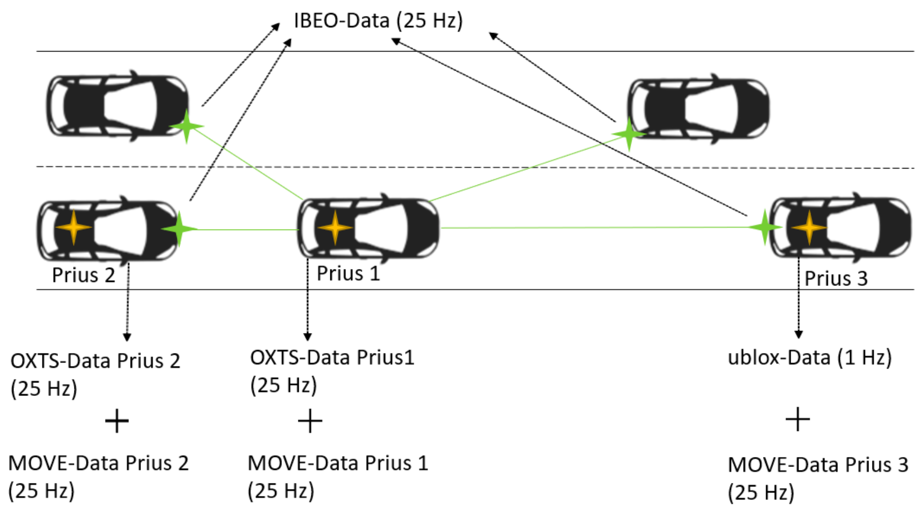


FIGURE 1 : Data Sources

METHODOLOGY

As stated above, the basis of this work is the data analysis from two autonomous test vehicles. These vehicles basically know two automated longitudinal control systems, Cooperative Adaptive Cruise Control (CACC) and degraded Cooperative Adaptive Cruise Control (dCACC). The term CACC denotes automated longitudinal control systems that use communication with the leading vehicle for determining the own acceleration. In the system used in CoEXist, three different settings of the time headway were possible: 0.3, 0.6 and 1.0 s.

Degraded CACC (dCACC) stands for the following behavior in autonomous mode when there is no communication with the leading vehicle. According to the documentation of the data collection, although the controller does not have internal information about the leading vehicle's state, it tries to predict its behavior for adjusting the own speed (*18*).

While the speed of each test vehicle was given directly from the sensor data, the net distances were not provided. Therefore, we had to retrieve the net distances from the positional data of the test vehicles. There are 4 different data sources (*18*):

- The ublox data: the ublox system is a GPS sensor providing position data for Prius 3 at a frequency of 1 Hz. The accuracy is at least 1 m.
- The MOVE data: The MOVE system is an interface between the vehicle CAN network and an external platform. It provides information from the vehicles' sensors motion and internal state for Prius 1, 2 and 3, respectively.
- The OXTS RTK-GPS data: OXTS-RTK is an inertial and dual antenna GPS system with a high accuracy of 0.01 m. It provides information about the vehicles' position, orientation and motion for Prius 1 and 2, respectively
- The IBEO data: The autonomous vehicles are equipped with six IBEO LUX 4 LiDAR sensors that provide a 360° view of the vehicle's surroundings. For Prius 1, the system's output is given as position data of the surrounding vehicles.

The data was preprocessed by TASS international in the sense that the raw sensor data was filtered for random noise. For every test run, each of which contained one or two scenarios, there are 7 different data files, one for each data source and vehicle (see figure 1). We combined the data from the different data sources into one data set per test vehicle.

The net distances were calculated using the position data from the IBEO datasets, i.e. the distances to the surrounding vehicles as "seen" by Prius 1. As the test drives were conducted on a public road, i.e. in a normal traffic situation, the Prius 1's sensor detected all vehicles traveling around it. This approach made it possible to assure that situations, when normal vehicles interfered with the test vehicles, were filtered out from the results (because also normal vehicle positions appear in the data, not only the positions from the test vehicles). Consequently, we had to filter the preceding vehicle and the following vehicle of the Prius 1 from the various vehicles detected. For the filtering algorithm, we used the heading angle of Prius 1 and the position data from the other test vehicles.

To produce reliable results, the data sets from the preceding steps were filtered afterwards, so that only situations were considered when the systems were running normally. A "normal" situation was defined as follows:

- Autonomous mode was switched on and working
- The system was not overridden by the human test driver
- The system is in "following mode" (e.g. the following vehicle is not "lost" at a traffic light)
- The following procedure is not interfered by another vehicle cutting in.

This was accomplished by checking the internal state variables from the MOVE data sets. The data processing is described in detail in the CoEXist technical report (*18*).

The most important parameters in the Wiedemann model for adjusting the following behavior are the standstill distance (CCO) and the time gap between leader and follower that the driver tries to keep when driving (CC1). The vehicle aims at keeping the safety distance given by $d_{safe} = CC0 + CC1 \cdot v$. The standstill distance has a great influence on capacity at intersections while the time gap is decisive for capacities on links. In the case of the autonomous vehicles, the target values of the time headway are given by the user setting. In contrast to that, the driver can't adjust the standstill distance of the test vehicles. Consequently, the documentation provided no information about the target standstill distance. Therefore, we had to derive the target standstill distances from the data.

Once standstill distance and time gap are known, the remaining question is, how exactly the control logic of the autonomous vehicles work, i.e. in which situations the desired headway is not met and how much the behavior can deviate from the standard behavior. From a theoretical point of view, various reasons can be found for deviating from the target rules in certain situations, as there exists a variety of possible optimization objectives: e.g. safety, fuel saving, passenger comfort or stability of traffic flow. Accordingly, we examined the course of the headway between the vehicles over a test run. We derived characteristics of the automated car following that served as input for calibrating the Wiedemann parameters.

The time headway describes the time the following vehicle needs to reach the position of the vehicle in front at a given point in time if the following vehicle continues to travel at the same speed. Because time headway cannot be measured directly and constantly over time, the net following distance and velocity were plotted for each time step. Dividing the distance by the speed in m/s gives the actual time headway. Thus, a linear relationship between the two parameters implies a constant time headway, when the standstill distance is neglected. All headways are given as net headways, which means that the reference points are the rear bumper of the leading and the front bumper of the following vehicle.

Vissim provides two different car following models, Wiedemann 74 and Wiedemann 99. Both are so-called psycho-physical models, which means that the model considers human shortcomings in the perception of speeds and distances and in operating the car. That's why the distance oscillates around a target time headway (see figure 3c). This human behavior had to be adjusted to modeling the deterministic behavior of the test vehicles. Wiedemann 99 allows for changing many of its parameters and assumes a linear relationship between speed and following distance (i.e., a constant time headway plus standstill distance). Furthermore, in contrast to Wiedemann 74, the vehicles keep their exact desired speed when no vehicle in front influences their behavior. In conclusion, Wiedemann 99 is more suitable for simulating autonomous vehicles.

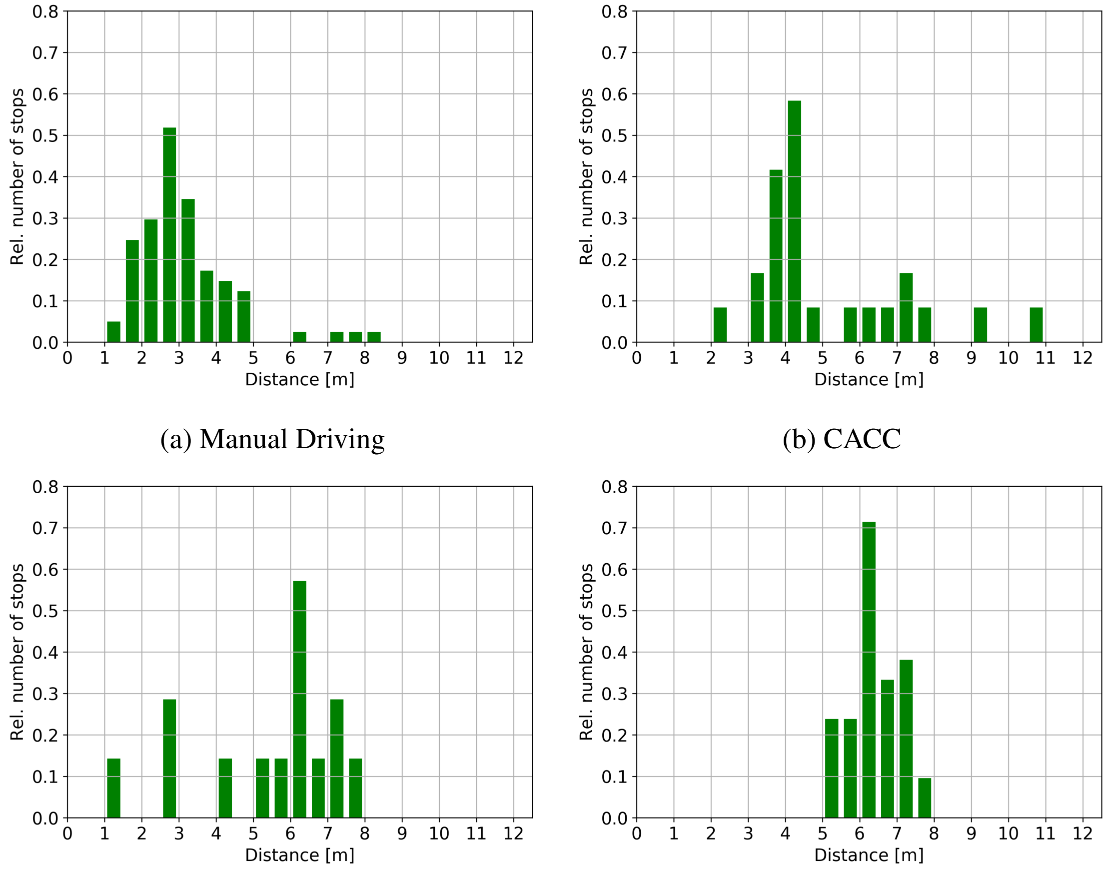
For analyzing the Vissim behavior, we replicated the test track in Vissim and simulated the three test vehicles following the test route without any interferences. For the two following autonomous vehicles we defined adjusted parameter sets. We modeled the following process by opening only one lane for the vehicles and setting the desired speed of the two following vehicles higher than that of the first one. Because the vehicles' behavior is no longer of a stochastic nature but deterministic, it is not necessary to reproduce each scenario and to analyze the statistical measures resulting from the different experiments.

FINDINGS

Figure 2 shows the standstill distances found in the test data. The data set was filtered by the different following situations when driving in autonomous mode. For reference, we included standstill distances from situations when the vehicles were manually driven (see figure 2a). Because it was not possible to derive directly from the data whether communication was switched on or not, we had to base the classification between dCACC and CACC on the scenario specification. We expect that deviations from these specifications occurred, e.g. because communication was not switched on during the entire test run. Thus, only for following a manually driven car, we assume correct classification of all data.

Figure 2b shows the standstill distance of following an autonomous vehicle in CACC mode. Figure 2c shows the same results when following another autonomous vehicle in dCACC mode. Figure 2d describes the standstill distances when following a manually driven car in autonomous mode (dCACC). The histograms show the relative number of stops per distance class. For manual drivers, the histogram has its peak at 3 m. The histograms for CACC (2b) and the two dCACC situations (2b and 2d) show a clear accumulation at about 4 m and 6 m, respectively. However, both the distributions 2b and 2c vary considerably and seem to comprise also data that fits better to the other one. We assume that this is due to misclassifications following from the above described lack of information about the communication status. This interpretation is confirmed by figure 2d. Following a manually driven car, communication is generally not possible. Accordingly, data clusters tightly around 6 m. Thus, we conclude that in CACC mode, the test vehicles aim at a standstill distance of 4 m. In dCACC mode, the target value seems to be 6 m. Variances seem to be similar in both cases. Overall, standstill distances are very large. Compared to Vissim default settings of CC0, measured standstill distances are 4 times higher in dCACC. Standstill distances are therefore underestimated in most studies simulating AVs.

As described above, we plotted the distance headways against the velocity for investigating qualitatively the time headway. For making visible the different driving situations of the test runs, e.g. braking in front of or accelerating after a traffic light, the colors of the data points represent the speed differences between the leading and the following vehicle. The speed differences are



(a) Manual Driving

(b) CACC

(c) dCACC Following AV

(d) dCACC Following Manually Driven Car

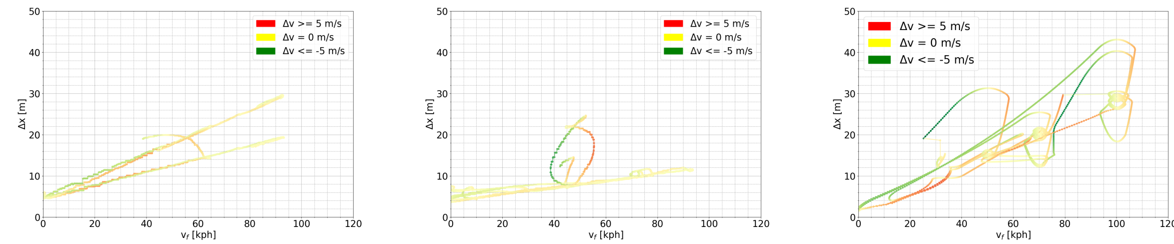
FIGURE 2 : Observed Standstill Distances During All Test Runs

denoted as $\Delta v = v_{following} - v_{leading}$. A negative Δv means that the following vehicle is slower. This usually happens if both vehicles accelerate due to a time lag in the reaction of the following vehicle. A positive Δv means that the following vehicle is faster, indicating that the vehicle in front brakes harder or earlier than the following vehicle.

When following another autonomous vehicle in CACC, the observed behavior meets well the target values. Figure 3b shows the following at a time headway of 0.3 s, figure 3a the following at 0.6 and 1.0 s. The big “loop” in figure 3b is due to a short communication breakdown between the vehicles. The following distance in general is equal to the standstill distance plus the desired time headway transferred to meters. However, there is some variance in the time headways. The figure also shows that this variance stems mainly from different standstill distances and not from oscillations during following.

This picture is in accordance with the findings from the analysis of standstill distances. In conclusion, both figures show deviations from the target values. These deviations are small in magnitude and usually do not appear when approaching the desired speed but occur at all speeds and when coming to a halt.

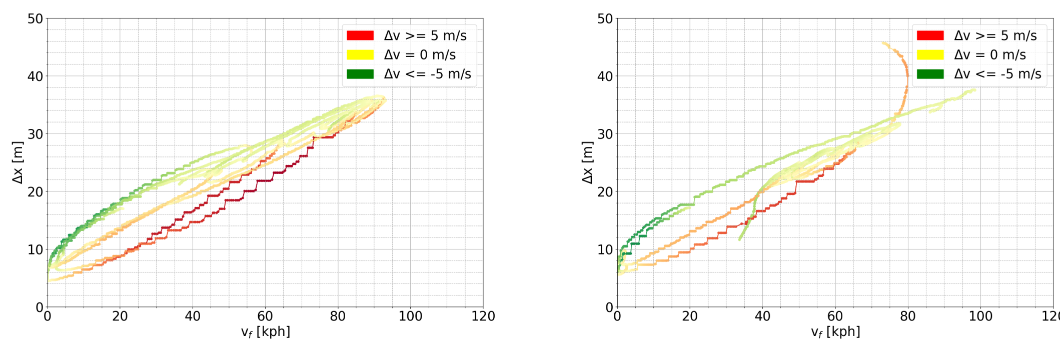
When following an autonomous vehicle in dCACC, the desired behavior of maintaining a fixed time headway plus standstill distance cannot always be met. From figure 4 it becomes clear



(a) CACC Following at Headway of 0.6 s and 1.0 s (b) CACC Following at Headway of 0.3 s (c) Vissim Default Following Behavior

FIGURE 3 : AV Following Behavior vs. Vissim Default Behavior

that the vehicles show larger headways than the target value when the follower is faster. It shows lower headways when the vehicle is slower. When the differences in the velocities are small, the distance is very close to the expected headway. In general, the data does not show much difference between the following behavior when following a manually driven vehicle and when following an autonomous vehicle in dCACC. Consequently, it is not necessary to differentiate between these two cases.



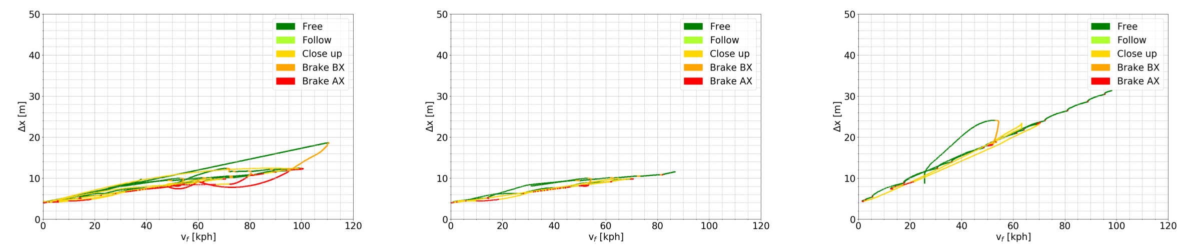
(a) dCACC Following AV (b) dCACC Following Manually Driven Car

FIGURE 4 : AV Following Behavior Without Communication

We conclude from the empirical data that especially in CACC mode, deviations from the target distance are small and are of a different nature than deviations from the target distance in Vissim. The typical oscillations that are produced by Vissim default behavior (see figure 3c) should thus be omitted completely. For dealing with the stochastic behavior creating the oscillations, a new feature was implemented by PTV, which allows for turning off all implicit stochastic components in the Wiedemann model (tick-box "Use implicit stochastics"). In a first step, we simulated the test vehicles by using this feature and adjusting the parameters of the Wiedemann model. In a second step, deviations from the behavior of the test vehicles were identified and adjustments of the acceleration behavior were made. In a third step, we compared the adjusted driving behavior again to the empirical data and evaluated the results. Table 1 shows the settings used for the autonomous vehicles compared to the Vissim default settings. Furthermore, we adjusted some distributions and settings:

TABLE 1 : Wiedemann 99 Parameter Settings for Simulating AVs

Parameter	Default behavior	Autonomous CACC	Autonomous dCACC	Unit
CC0	1.5	4	6	m
CC1	0.9	[0.3, 0.6, 1.0]	1.0	s
CC2	4	0	0	m
CC3	-8	-40	-40	s
CC4	-0.35	0	0	$\frac{m}{s}$
CC5	0.35	0	0	$\frac{m}{s}$
CC6	11.44	0	0	$\frac{1}{m \cdot s}$
CC7	0.25	0.25	0.25	$\frac{m}{s^2}$
CC8	3.5	3.5	3.5	$\frac{m}{s^2}$
CC9	1.5	1.5	1.5	$\frac{m}{s^2}$



(a) Without Adjusted Acceleration Procedure, H = 0.3 s

(b) With Adjusted Acceleration Procedure, H = 0.3 s

(c) With Adjusted Acceleration Procedure, H = 1.0 s

FIGURE 5 : Vissim Following Behavior For Different Time Headways (H)

- The distributions for desired acceleration and deceleration as well as for maximum acceleration and deceleration have to be a linear function in accordance with the vehicle's technical capabilities.
- Smooth close up must be enabled for all vehicles.
- The safety distance at traffic lights must not be reduced. In the default settings, it is reduced with the factor 0.6; this factor must be set to 1.0.

For analyzing the simulation results, again we plotted the distance headway against the velocity. The colors of the data points represent the different acceleration procedures in Vissim, called interaction states. In interaction state "Free", the vehicle accelerates towards its desired speed. In interaction state "Follow", the difference between target and actual headway is small and thus the acceleration is close to 0. In interaction state "Brake BX" and "Brake AX" the vehicles decelerates, as the distance to the leader is smaller than the target distance.
In interaction state "Close up", the vehicle detects a static obstacle (such as a traffic light) and decelerates towards it (*19*).

Figure 5a shows the following behavior in Vissim with time headway 0.3 s after adjusting the Wiedemann parameters as given in Table 1. It becomes clear that in general, Vissim produces a good fit of the autonomous behavior in CACC. The major problem is that, when accelerating over a large distance, the following vehicle cannot keep up with the leading vehicle. The vehicle is not capable of accelerating to such an extent that it keeps the headway of 0.3 s. Therefore, the following vehicle accelerates above the speed of the leading vehicle when the latter reaches its desired speed. Consequently, the following distance becomes smaller than the desired headway, which makes the vehicle break again until it meets the desired headway. For larger time headways, this problem did not occur. As a possible solution, we increased the acceleration capabilities for vehicles following an autonomous vehicle type. Figure 3b depicts the resulting change in behavior. Some deviations from the desired distance still occur, however, these are similar in magnitude to the deviations found in the empirical data. The biggest difference is that the standstill distance in Vissim is always exactly the value for CC0 while the standstill distances of the empirical data vary. For the case of following another vehicle without communication, the picture is different. Reproducing the observed high deviations from the target headway realistically is not possible by adjusting the Wiedemann parameters but would require the implementation of a new acceleration and deceleration procedure. Especially the large headways when accelerating from standstill have tremendous effects on capacity at nodes. A possibility for reproducing that effect is to implement a reaction time, so that the autonomous vehicle delays the start when driving after another vehicle without communication. However, one should keep in mind that the analysed behavior might not be representative. Figure 5c shows the following behavior in dCACC (following either an autonomous or a manually driven car). It is equal to the following behavior in CACC, with the only difference that the desired time headway is always 1.0 s.

CONCLUSIONS AND OUTLOOK

The analysis of the test vehicles' following behavior gave insight into their basic settings. The vehicles aim at the distance headway resulting from multiplying the time headway setting with the current velocity and adding the standstill distance. In CACC mode, a time headway smaller than 0.5 s is technically possible (at 120 kph the headway is 0.42 s). In dCACC mode, the headway setting is 1 s, which results in an actual headway of 1.18 s at 120 kph and 1.43 s at 50 kph. Standstill distances are very large (at least 4 m) compared to human drivers. The deviations from the target behavior are small in CACC, but considerable in dCACC. It would be desirable to reproduce these deviations in the simulation. However, this requires new approaches in the acceleration functions of car-following models, because the behavior differs fundamentally from the modeling of human acceleration behavior.

Simulations showed that, in general, CACC behavior is well reproduced by the Wiedemann 99 model. Very small headways can be problematic for simulating acceleration processes in Vissim 10, because of a certain delay in reaction to the leader's acceleration. A solution will be to propagate information about the vehicle's internal state throughout a platoon of AVs in future Vissim versions. We presented a parameter set for the Wiedemann model that is well suited for simulating CACC behavior on freeways. This is probably the most proximate scenario in automated driving. In urban traffic and mixed scenarios, CACC necessarily becomes dCACC in many situations, e.g. when a leader is lost at a traffic light or manually driven vehicles cut in. This requires changing the following behavior subject to the leading vehicle type. This is not implemented in Vissim 10 but will be available in future versions.

dCACC behavior is sufficiently reproduced when simulating free-flow traffic on freeways (i.e. when Δv is small.). In urban traffic or stop-and-go traffic, the delays when accelerating from stop are not reproduced in the simulation. This might lead to an overestimation of capacity especially at intersections. A possible solution would be to implement a reaction time when accelerating from stop, as it is already available in Vissim for vehicles in the first row. Apart from these problems, data is lacking for behavior towards static obstacles, such as an autonomous vehicle waiting in first row at a traffic light. This situation, like many others, was not tested in the experiments. Therefore, our results do not yet cover all driving situations in urban traffic. Apart from working on a changed acceleration behavior, results will also be tested in more detail. Future work in the ongoing CoEXist-project will include testing the results on other infrastructure elements. In general, uncertainties about AV behavior limit the universal validity of our results, e.g., we do not know whether the behavior of the two test cars is representative for commercially available AVs in the future.

Nevertheless, since empirical data from automated cars is hard to get, the presented work is valuable for improving and validating AV modeling in Vissim. Furthermore, the aim of this research was not modelling the observed behavior exactly but deriving general assumptions about AV car following behavior and testing the Wiedemann model for applicability on AVs. In future research we plan to quantify the deviations of the Wiedemann behavior from the observed behavior and to compare in more detail the acceleration profiles. The next important step in improving the model will be to investigate the reaction to "disturbances", i.e. when another vehicle cuts in at a small distance or if communication is interrupted. This might also be an important factor for assessing capacities in mixed traffic.

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AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows (in alphabetical order): study conception and design: P. Vortisch, V. Zeidler; modeling and simulation: L. Kautzsch, V. Zeidler; analysis and interpretation of results: H. S. Buck, P. Vortisch, C. M. Weyland, V. Zeidler; draft manuscript preparation: H. S. Buck, L. Kautzsch, P. Vortisch, C. M. Weyland, V. Zeidler. All authors reviewed the results and approved the final version of the manuscript.

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